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FEATURE REPRESENTATIONS FOR MONITORING OF TOOL WEAR

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ABSTRACT

We address the general problem of reliable, real-time detection of faults in metal-removal processes in manufacturing. As has long been recognized by skilled machine operators, mechanical and acoustic vibrations can be reliable sources of cues for such monitoring. However, conventional dull-tool monitoring systems, which are generally based on stationary signal processing methods, are inadequate for real-time control of drilling procedure. Making use of a database from nine different drill bits, we a) identify different features which seem to contain tool wear information, b) document what we found to be superior signal processing tools to identify, extract and process these non-stationary features, and c) stress the need for a fully annotated public-domain manufacturing signal database.

1. INTRODUCTION

An important problem in the area of manufacturing signal processing is to continually monitor metal-removal processes and detect changes whenever, and as soon as, they occur. As has long been recognized by skilled machine operators, mechanical and acoustic vibrations are reliable sources of cues for such monitoring. The ultimate objective of automatic tool wear monitoring is not simply to outperform the ability of the operators' ears in recognizing tool wear, but to go one step further and detect it quickly enough to take preventive action.

However, it is not clear where the signatures of the processes are located in the acoustic signal, and how different states of a single process show up in the signal. How does tool wear manifest itself in the vibration signal? How does the geometry of a tool (e.g. the drill bit) affect the signal? What about the effects of noise from the surrounding industrial environment?

In this paper, we take the first few steps towards answering these questions by

a) translating the needs of process monitoring into signal processing problems,

b) pinpointing certain features which characterize the nature of certain processes and/or their current states,

c) assembling some non-stationary signal processing methods that are useful in processing these features, and

d) stressing the need for a public, fully annotated, manufacturing signal database.

2. BACKGROUND

Process Monitoring Sensor Signals: For effective process control, researchers rely mainly on non-invasive, indirect measurements such as thrust forces, cutting forces, drilling forces, temperature, acoustic emissions, or a combination of the above [1]. A comparison of some of these measurements is provided in [2]. Heck [3] argues that multiple sensor inputs are required for reliable monitoring.

Signal Analysis: Najafi and Hakim [4] have compared various standard non-parametric spectral estimation techniques applied to machine vibration data. Ramirez and Thornhill [5] analyze the drilling forces signal and its spectra for use in monitoring circuit board manufacture. Kittel and Hayes [6] present a symbolic signal representation for process monitoring signals. Fang, Atlas and Bernard [7] have made use of quadratic energy detectors to accurately detect temporal events in acoustic emissions from drilling a composite honeycomb sheet. In this paper, we continue to show how non-stationary techniques can provide good feature representations for monitoring of tool wear.

3. DATA DESCRIPTION

Acoustic vibrations of a machine drilling holes in metal were sensed using an accelerometer. The resulting analog output was passed through an anti-aliasing filter with a corner frequency of 16 KHz., and then sampled at 40 KHz. Such data was taken from holes drilled by nine individual drill bits of two sizes. For this work, we have concentrated on the "break-in" region, which we define as the portion between the instant when the drill touches the metal and the instant when the cutting edges of the bit are buried in

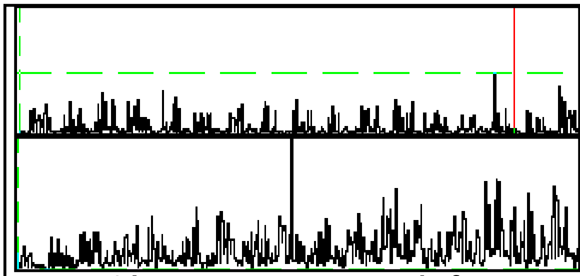

Figure 1: A long-time measure vs. time. The figure on top is a time-series from a sharp hole; the bottom is from a dull hole. Each point in the series above represents one revolution of the drill bit. Each series contains 497 points.

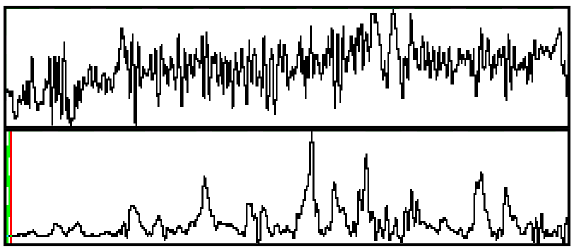

Figure 2 Example of a short-time measure which preserves the fine time structure of data from a sharp (top) and a dull (bottom) hole. Each of the two time-series represents one revolution of the drill bit.

the metal. Break-in is rich with non-stationarities carrying informative short-time events, while being early enough in the hole-drilling process to be able to avoid damage if the system determines that a bad hole is about to be drilled.

4. PROBLEMS AT HAND

We have found the two problems below to be of key importance in the monitoring of tool wear:

a. **Energy detection:** In metal-removal processes, the energy increases in certain frequency bands are seen to correlate with tool wear [8]. We have found that two energy measures are important in this case -- a fairly long-time measure (e.g., averaged over one revolution) indicating the state of the tool (Fig. 1), and a short-time energy measure (e.g., 100 per revolution) which preserves the temporal structure of the band of interest and which is likely to contain detailed information about the nature of the wear (Fig. 2). Conventional energy measures (like the linear filter followed by a squarer and a low-pass filter) fail to provide reliable short-time measures owing to their smearing in time.

b. **Transient detection:** Events like chipping, tool fracture and tool breakage manifest themselves in the signal as short-lived transients [3]. Detection of these transients, i.e. sacrificing temporal resolution, is necessary to monitor and prevent such events.

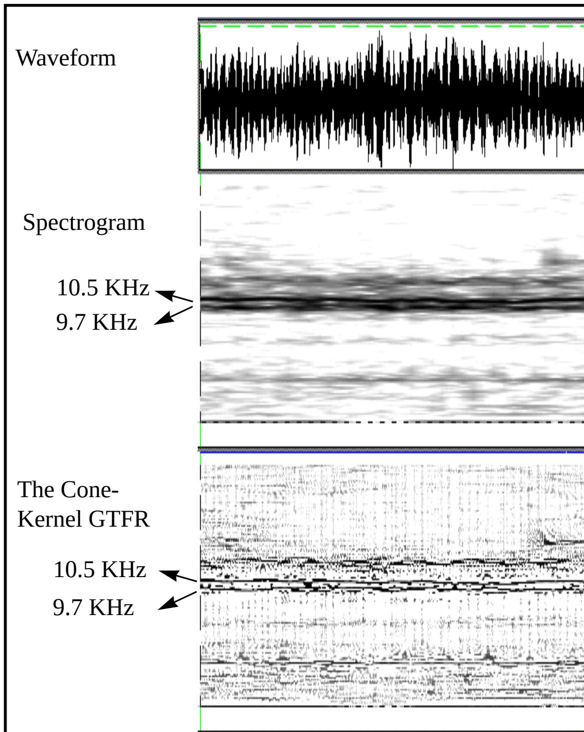

Figure 3: Spectrogram and Cone-Kernel GTFR of a portion of the drilling time-series. The Cone-Kernel exhibits more temporal structure than does the spec-

5. FEATURE ANALYSIS

As a first step towards feature extraction and processing, the overall time and frequency structures were visualized using generalized time-frequency representations (GTFR). Fig. 3 shows (from top to bottom) a portion of the raw time series, its spectrogram and the cone-kernel GTFR [9]. The spectrogram and the cone-kernel both place the interference terms on top of the auto-terms (frequencies which are really present in the signal) *and* attenuate them (unlike other time-frequency representations like the Wigner Distribution) [10]. However, since the cone-kernel does so without suffering from a time-frequency trade-off as the spectrogram does, it is expected that time-frequency structures are portrayed more accurately. And Fig. 3 indeed shows the cone-kernel resolving the two closely-spaced frequency components better, while simultaneously revealing more of the fine temporal structure on each of them.

We find the following essential features correlate strongly with drill dulling:

a. *The average energy in the lower of the two closely spaced frequency components of Fig*. 3.

b. *The amplitude modulation (AM) of the upper frequency component*.

c. *The distance between the two frequency components.*

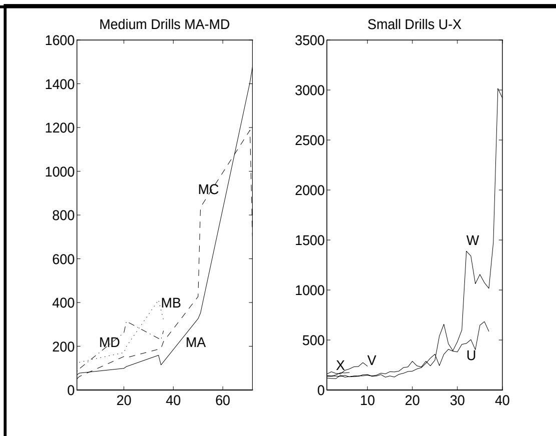

Figure 4: Average power in the band of interest (around 9.7 KHz) for small and medium drills as a function of hole number. Each curve represents the data available from the lifetime of a single drill bit.

The average energy in the lower frequency component (9.7 KHz) is plotted in Figure 4 as a function of hole number for eight drill bits of two different sizes. The figure indicates that the average energy in the 9.7 KHz band may be strongly correlated with drill dulling.

6. HIGH-RESOLUTION FEATURE DETECTORS

If detecting drill dullness were our only aim, long-time features like the one plotted in Fig. 4 would be sufficient; tracing the fine temporal structure of the AM would not be critical and time-smearing that conventional filters introduce could be tolerated. However, isolating frequency bands and then capturing temporal detail is key to understanding the phenomena behind drill dulling and control it in real time. Generalized quadratic detectors fit this need.

The quadratic detector [11] is an energy detector which integrates frequency filtering. The finite duration discrete version of the generalized quadratic detector is

$$y[n] = \sum_{m_1=-M}^{M} \sum_{m_2=-M}^{M} q[m_1, m_2]\, x[n-m_1]\, x[n-m_2] = \boldsymbol{x}[\boldsymbol{n}]^T \boldsymbol{Q} \boldsymbol{x}[\boldsymbol{n}] \tag{1}$$

where $\boldsymbol{x}[\boldsymbol{n}]$ is a column vector of $2M$+1 samples of the real input signal $x[n]$ and the $(2M+1)\times(2M+1)$ matrix $\boldsymbol{Q}$ with elements $q[m_1,m_2]$ is the quadratic kernel. Our methodology for determining this kernel is to analyze the effects of properties on the mathematical structure of the kernel, and then determine the kernel through choices of, and compromises between, properties for specific applications. Some of the desired properties of an energy detector are listed in Table 1. Considering only the properties of frequency interference elimination, finite time support, and time-frequency resolution independence, a simple quadratic detector is designed by taking the kernel of the shape [⬮], i.e.

Table 1: Desired properties of the quadratic detector and the corresponding constraints on the matrix $\boldsymbol{Q}$

Properties	**Constraints on Q**
non-negative output	positive-semi-definite
finite time support	non-zero in blocks along the cross-diagonal ([▞]) or only in the cross ([+])
no nonlinear frequency interference	Toeplitz
independent time and frequency resolution	non-zero only in the cross-diagonal ([/])

$$y[n] = \sum_{\substack{m_1=-M \\ |m_1+m_2| < \frac{L+1}{2}}}^{M} \sum_{m_2=-M}^{M} h[|m_1-m_2|]\, r[n, m_1, m_2] \tag{2}$$
$$r[n, m_1, m_2] = x[n-m_1]\, x[n-m_2]$$

where $2M > L$, L is the number of non-zero bands in the cross-diagonal direction. $h[m]$ is a $(4M+1)$-point set of symmetric quadratic coefficients (i.e. $2M$+1 unique values) which can be chosen using standard FIR filter design procedures. This detector not only suppresses noise, but also provides high resolution in both time and frequency. Moreover, the structure of the detector allows recursive techniques to be used for real time implementation, with the number of computations less than that of a standard energy detector with the same number of coefficients.

In Fig. 4, the drill data contains two closely spaced frequency components 10.5 KHz and 9.7 KHz. To track the energy variations of these two frequency components, two simple quadratic detectors were designed with bandwidths of 500 Hz and 800 Hz, and center frequencies of 9.7 KHz and 10.56 KHz, respectively. For comparison, a standard energy detector was designed with the same set of coefficients as the quadratic detector with a bandwidth of 500 Hz and a center frequency of 9.7 KHz. The outputs show that the quadratic detector captures more temporal detail than the standard energy detector and is capable of separating two closely spaced frequency components. This ability to remove noise, provide fine frequency selectivity, and simultaneously resolve temporal detail exemplifies the key advantages of these non-linear detectors.

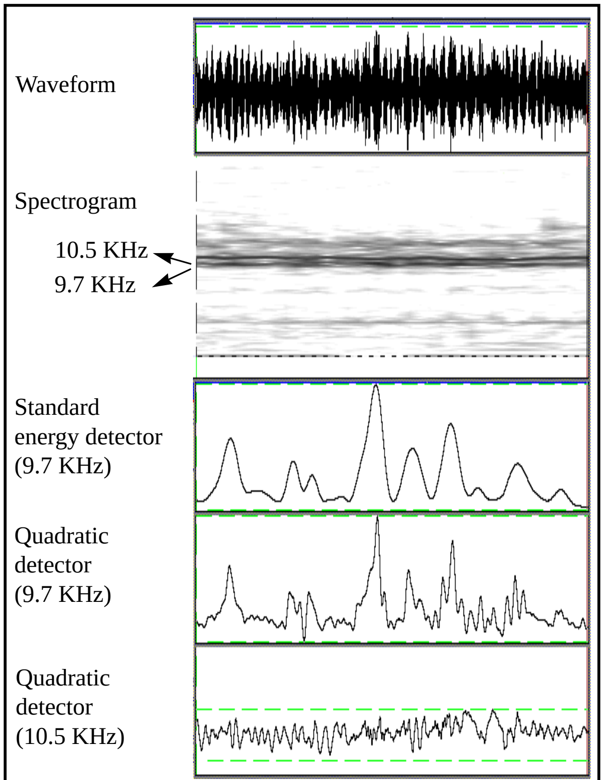

Figure 5: Performance of compromise quadratic detectors for temporal detail extraction between two closely spaced frequency components. *Note the improved temporal detail of the quadratic detector.*

7. NEED FOR A PUBLIC-DOMAIN DATABASE

A serious problem arises at this point. Having worked with the available data and being convinced that we have the right tools which capture useful features, we are faced with the problem of not being able to compare our results with those of others due to the lack of a common platform. The need isn't just one of common data. The manufacturing signal processing field also needs a set of definitions of performance measures. For instance, in the context of drilling, hole quality may be measured in several different ways (accuracy of the diameter, smoothness of the edge, interior surface finish, etc.) and a combination of the various properties of the hole made should go into the definition of hole-quality. Thus, it is essential that a fully annotated, public-domain, manufacturing signal database and an associated set of "standards" be developed analogous to the ones used by the speech community [12]. If such a database were made available, signal processing researchers would make substantial contributions by bringing to the field a variety of non-stationary analytical techniques and front-ends applied to their needs.

8. CONCLUSION

Manufacturing signal processing has made great strides in recent years. But most of the work in this area, along with the monitoring systems available, have focussed mainly on the stationary parts of the data (for example, the region after break-in). We have made progress with the more difficult task of finding features in the non-stationary portions of the signal. The creation of a public database containing labelled data from various types of manufacturing processes would not only enable a comparison of our work with that of others, but would also encourage more researchers to apply their methods to manufacturing needs.

9. ACKNOWLEDGEMENTS

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